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Location-Based Mobile Gaming and Local Depression Trends: A Study of Pokémon Go

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ABSTRACT

Emerging literature has begun to investigate the role of technology in public health. Yet, a minimal amount is understood about whether, how, and why digital games, notably mobile games, might affect mental health, particularly depression. In this work, we examine the effect of location-based mobile gaming on local depression trends. We measure population-level depression using a well-established mechanism from the medical and public health literature, internet search of depression-related terms. We argue that the introduction of Pokémon Go, a mobile game that encourages outdoor physical activity, face-to-face socialization, and exposure to nature, may alleviate non-clinical forms of mild depression for users playing the game. To identify the effect, we employ a difference-in-differences approach to exploit the staggered release of Pokémon Go into 166 regions in 12 English-speaking countries. We empirically document a disproportionate decrease in depression-related search in those regions where users are able to play Pokémon Go. This finding lends credence to anecdotal claims that location-based mobile games may alleviate symptoms of depression of their users, underscoring the mental health opportunities of location-based mobile gaming and creating new opportunities for information systems research.

KEYWORDS

Location-based mobile games; mental health; depression; search query data; natural experiment; difference-in-differences; mobile games; digital games

Introduction

Emerging literature at the intersection of information systems and public health has begun to intensely discuss the effects of digital technologies on public welfare and population health. In such studies, researchers examine a wide variety of questions, such as how search engine query data can be used to detect and monitor influenza epidemics [47], how online health communities provide support for users with chronic diseases [49], and how digital platforms attenuate drunk driving [50]. Research has also begun to examine if digital technologies have had a deleterious effect on public health, including the spread of sexually transmitted diseases [24], drug abuse [67], and obsessive-compulsive disorder [58]. In this study, we focus on an emerging digital artifact, location-based mobile games, and their

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potential to affect a notorious public health issue, depression, one of the most common mental and emotional disorders characterized by "persistent sadness and a lack of interest or pleasure in previously rewarding or enjoyable activities" [110].

Defined as games played on a mobile device, such that the gaming experience is based on the player's location [63], location-based mobile games have received significant attention in the academic and practitioner literature [104]. Accounts from scholars and the popular press have identified several effects wrought by such games, some of which would seem to ameliorate the widely-acknowledged adverse health effects of traditional gaming (e.g., selfisolation, addiction [100]). These include promoting outdoor physical activity, face-to-face socialization, and interaction with nature (e.g., [2,21,51]), all of which alleviate obesity¹ and ease social isolation.² Recent accounts have even raised the prospect that location-based mobile games (e.g., Geocaching, BotFighters, Ingress) may influence their users' moods [69]. Grohol [51], for example, performed a content analysis of users' tweets, showing that users were less anxious when playing location-based mobile games, a finding corroborated by anecdotal reports also made by McCartney [73] and Tateno et al. [107]. Although these studies show suggestive evidence of the benefits of location-based mobile gaming for their users' well-being, it is crucial to subject such anecdotal claims to rigorous empirical scrutiny. In this study, we explore the prospect of mobile games to alleviate depression by asking: Do location-based mobile games affect local depression trends?

The importance of investigating depression at the population level should also be emphasized given its non-trivial economic and human toll. According to the World Health Organization [110], depression affected 264 million people worldwide in 2020—3.4 percent of the global population. In the United States, 51.5 million adults (nearly one in five of U.S. adults) suffered from mental illness in 2019 [78], and 17.3 million U.S. adults had at least one major depressive episode (63 percent of which experienced severe impairment [77]). Economically, depressive disorders are the sixth-most-costly health condition overall, with U.S. spending about \$71 billion annually as of 2016 [35]. It should thus come as no surprise that depression poses significant challenges for individuals, organizations, policymakers, and society at large.

In this study, we examine the effects that location-based mobile games may have on the prevalence of the most common form of depression, that is, emotional distress or nonclinical depression [25]. It is important to separate these types of depression from each other, and our focus on acute non-major depression is deliberate. While it is plausible that the symptoms of more moderate depressive disorders like anhedonia and melancholia might be alleviated through positive behavioral changes such as exercise and socialization, it is implausible that chronic or severe depressive disorders (such as those that lead to self-harm) might be; these disorders often require pharmacological or psychotherapeutic intervention.

To identify any effect of location-based mobile gaming on local depression trends, we exploit the phased rollout of Pokémon Go into 166 regions of 12 English-speaking countries in 2016. In doing so, we take advantage of the game's staggered release pattern³ using a difference-in-differences approach. This provides several benefits, the primary one being the creation of a natural control group, i.e., those locations where Pokémon Go has not yet been released. Following extensive research in the public and population health literature [6, 17, 22, 47, 80, 108], we capture local trends in depression using Google Trends data of the Google Misery Index, that is, the prevalence of common depression-related terms (i.e.,

"*depression*," "*stress*," "*anxiety*," "*fatigue*").⁴ We then validate the coverage and accuracy of our measures by expanding the set of search terms using Brynjolfsson et al. [18]'s "Crowd-Squared" approach and correlate our measures with administrative data from the U.S. Centers for Disease Control and Prevention (CDC) and the Global Health Data Exchange (GHDx). A battery of falsification tests yields consistent results.

Our empirical analyses indicate that the release of Pokémon Go is associated with a significant short-term decrease in depression-related internet search, suggesting that location-based mobile games may decrease the prevalence of local rates of depression. This finding lends credence to anecdotal reports that the game may alter the mood of location-based mobile gamers [51, 107]. Importantly, while this effect exists with depression-related search, we observe no evidence for the correlation between the game release and suicide-related search (i.e., "suicide," painless suicide," "how to suicide," "how to kill yourself"), suggesting that more severe forms of depression are less likely to be alleviated by mobile games.

We further delve into the theoretical mechanisms by which the effect might manifest. Extant research suggests three plausible mechanisms through which depression might be reduced by location-based mobile gaming. First, these games encourage players to be physically active [2]. Medical research has widely documented the mental health benefits stemming from physical activity (e.g., [86]). Intuitively, the physical activity enabled by location-based mobile games should yield similar benefits. Second, location-based mobile games create opportunities to socialize offline through gameplay [104]. Research indicates that when people interact in person and share experiences (e.g., about gaming) more actively, their symptoms of stress and anxiety are subsequently diminished [60]. Third, such games motivate people to go outdoors and interact with nature [69]. Research shows that even innocuous exposure to nature in parks and public greenspaces generally alleviates depression by reducing common risk factors associated with depression, most notably rumination [14], that is, repetitive thought on negative aspects of oneself. Our results show supportive empirical evidence of all three mechanisms. We also observe an opposite effect (i.e., an increase in depression-related search) when a digital game without the aforementioned mechanisms is introduced.

Several contributions stem from this work. First, we study an under-researched digital artifact—location-based mobile gaming—and its potential role in an important public health problem, that is, depression. A growing Information Systems (IS) literature has documented the potentially deleterious effects of digital technologies on public health (e.g., the spread of sexually transmitted diseases [24], drug abuse [67], and addiction [100]). Kyung et al. [59] even find that the proliferation of mobile internet is associated with an increase in suicide rates (as a function of suicide-related search). While much attention has focused on negative externalities of IT, we examine a potential public health benefit of IT (e.g., [47, 50, 84]), and we provide evidence that location-based mobile games may alleviate depression by facilitating outdoor physical activity, face-to-face socialization, and exposure to nature.

Relatedly, we contribute to the IS literature on gaming [52, 55, 64, 66, 83, 96, 102, 109]. While this literature has examined ways to mitigate the adverse effects of digital games [52] and incorporate gaming into the workplace [102], a minimal amount of consideration has been given to the public health implications of gaming and location-based mobile games. This study extends the discussion of the positive effects of gaming from online to offline

socialization [39, 42]. This work also contributes to the burgeoning IS literature (e.g., [1, 24, 28, 44, 49, 50, 67, 68, 84]) on the broader societal impacts of IT, by suggesting that search query data may be able to improve the monitoring of population-level depression and estimating its prevalence [47, 80].

Second, we contribute to the literature on population health [11, 32, 70, 71, 81, 95] by proposing the prospect of location-based mobile gaming to help cope with public concerns over depression, at least in its mild forms, by encouraging a healthy lifestyle. Although this finding must be corroborated by medical professionals to identify robust individual effects in the long term, our work highlights a potential, and hitherto unexplored, option for public health officials in the form of complementary approaches to alleviating depression. Notably, location-based mobile games might be leveraged to encourage positive behavioral changes, specifically outdoor physical activity, offline socialization, and nature-connected lifestyles.

Finally, practical implications stem from this work. For policymakers, we raise the potential for location-based mobile games to help ease depression and highlight a realtime and inexpensive means by which population levels of depression might be monitored (i.e., internet search data). Due to the ease of use, relatively low cost, and high accessibility, location-based mobile games may be attractive subsidy targets for policymakers. This is important given the ever-increasing economic burden of healthcare for depression. For game developers, our work shows the benefit of game features which encourage physical activity, offline social interaction, and exposure to nature. With the benefits from these activities, such features may help people pursue healthy lifestyle in a proactive way to cope with depression.

Background and Theory Development

In what follows, we provide an overview of various streams of literature that inform our question. First, we review the IS literature on digital gaming, including an extensive discussion of research on location-based mobile games. Second, we zoom out and discuss the epidemiological effects of IT, with a focus on mobile technology and public health. We then briefly review research on depression, including its causes, symptoms, and treatments. Finally, we integrate the IS and public health literature on non-medical treatments for depression and theorize the relationship between location-based mobile gaming and local depression trends.

Digital Gaming and Location-Based Mobile Games

This line of research has documented the positive and negative effects of digital gaming across contexts and investigated different gamification elements for meaningful engagement of users. Several streams exist.

In the first stream, IS scholars have held the assumption that online and mobile games may have adverse effects on well-being and investigated factors that mitigate or exacerbate harm. Chen et al. [26], for example, discuss the consequences of problematic smartphone game use—including a decrease in work/study performance and an increase in social isolation—as well as mitigation strategies via game design. Similarly, Xu et al. [111] stress the concern of addiction to online gaming among adolescents. They find that mental health issues, like social isolation and a need for escapism, can intensify such addiction, while education and attention-switching activities can mitigate addiction. In contrast, work exists on the positive social effects of digital gaming. Fayard and DeSanctis [39] show that language games allow for constructing collective identity, leading to a sense of "we-ness." Furthermore, Franceschi et al. [42] show that virtual worlds enable university students to meet and interact with each other, facilitating a sense of group and high engagement in group learning.

Beyond investigations of digital gaming and well-being, scholars have sought to understand how to manage user engagement either in a gaming context or in the workplace. Game developers face an inherent tension: more gaming leads to increased revenues but can also lead to issues of addiction for gamers. Research explores this tension. Huang et al. [55], for instance, show that curtailing player experience to a player's engagement level can increase gameplay, and therefore revenues. Still, other scholars have shown ways of increasing revenues without excessive gameplay (e.g., out-game markets for virtual currency [52]). Unsurprisingly, managers have sought to bring the benefits of gamification into the workplace as well [66, 102]; exploring the effects of game complexity, competition, and collaboration on engagement with, and efficacy of, various workplace activities, for example, employee training [64, 93, 96]. Essential in this research stream is that gamification extends well beyond hedonic activities, and can drive meaningful engagement in the workplace [102].

Despite the richness of this literature, digital gaming research has devoted conspicuously little attention to either the location-based elements of mobile gaming or how their unique design features might influence the psychological state of their users. Similar to traditional games, location-based mobile games might facilitate social interactions and promote health outcomes [4]. Yet, mobile games, be they location-based or not, are also known to be highly addictive, which leads to health issues. This dilemma brings a natural tension in the literature to bear. Beyond IS, the literature on digital gaming, and specifically location-based games, from other fields has shown mixed effects on health (broadly defined).

On the one hand, Ayers et al. [8] and Faccio and McConnell [38], raise concerns of addiction. There are also concerns of game-led distraction for drivers and pedestrians, and the subsequent risk of injuries and fatalities [38]. On the other hand, Howe et al. [54] and Nigg et al. [79] have identified a significant increase in physical activity (and a decrease in sedentary behaviors) after individuals start to play Pokémon Go. Indeed, Pamuru et al. [83] even find that the footprint made by players of location-based games can revitalize local businesses and restaurants. Yet, despite these differences, the mechanisms by which a change in behavior might manifest remain unclear, as do the technological features of games that might play a role in mental well-being. In what follows, we zoom out of the digital gaming literature and review the broader literature on the relationship between technology⁵—in particular, mobile technologies—and public health.

Mobile Technology and Public Health

Scholars have mostly examined the potential of mobile technologies (e.g., telehealth, selfhelp/fitness apps) to improve health [4]. Ghose and colleagues [46], for example, conducted an experiment on diabetes patients; finding that the adoption of a mobile health (mHealth) app can reduce blood glucose levels, hospital visits, and medical costs. They also find that the mHealth technology helps track, educate, and make diagnoses, thereby allowing patients to self-regulate their health behavior with less intervention. Yet, the implications of mHealth technology do not only stem from individual use. Instead, they can come from positive externalities because of a network of individuals who use technology together. For example, Aral and Nicolaides [4] find contagion patterns from the use of mobile fitness apps, in which users can view the exercise activities of their peers. This suggests that the social features of mobile apps bring about peer influence and create contagious health benefits.

However, while a large literature has focused on the potential of mobile technologies to improve population physical health, limited research has examined their mental health benefits. Nevertheless, extant research suggests several means by which such technologies may help to alleviate depression. These include, but are not limited to, lower treatment costs [33], personalized care [40], increased continuity and quality of care [87], and creating an environment that yields diminished stigma for patients [91]. The recent investments in smartphone apps by the U.S. Department of Veterans Affairs and the Department of Defense are perfect examples. Both agencies recently invested in apps to help caretakers monitor and treat veterans with post-traumatic stress disorder.⁶ In both cases, mobile health interventions helped caretakers reach patients more quickly and the latter to reduce the stigma of visiting a psychiatrist's office. More broadly, such interventions can be leveraged to enact medical treatments, such as telephone-delivered cognitive behavioral therapy [15], and treatment for depression [95]; as well as non-medical interventions, such as social support forums [10,27], consumer health wearables [85, 88], and exercise and fitness apps [4, 89, 95] (for a review of exemplary studies on technology and health, see Table A-1 in the Online Supplemental Appendix A). These interventions document the health benefits of technology, implying not only the prospect of location-based mobile games in easing depression, but also the need for a deeper understanding of depressionand its causes, symptoms, and treatments-among IS scholars.

Depression: Causes, Symptoms, and Treatments

According to the World Health Organization [110], depression is the most common mental disorder worldwide and a leading cause of disability. Depression results in feelings of sadness and a loss of interest in activities once enjoyed, leading to various emotional and physical problems.⁷ Broad consensus indicates depression is a mental disorder that can be influenced by genetic characteristics, changes in hormone levels, certain illnesses, stress, grief, and substance abuse [16, 34]. Degrees and symptoms of the depressive condition can vary widely, ranging from no impairment, to mild and moderate symptoms, to severe depression which results in persistent sadness, anxiety, feelings of emptiness, pessimism, irritability, and even self-harm [31]. Medical treatments for depression are diverse, ranging from traditional therapeutic interventions, for example, pharmacological intervention⁸ and psychotherapy,⁹ to more aggressive treatments, for example, electroconvulsive therapy [65].¹⁰

In addition to medical treatments, non-medical approaches to easing depression exist. Research to date has highlighted multiple behavioral changes which can yield positive impacts. These include: promoting physical activity, encouraging face-to-face socialization, and interacting with nature [14, 32, 60]. Physical activity has been shown to have many benefits for patients, inasmuch as regular exercise brings positive changes to the brain and

promotes feelings of well-being. Exercise also helps release endorphins, chemicals in the brain that inhibit the transmission of pain signals and produce feelings of euphoria [32].¹¹ Face-to-face socialization reduces feelings of isolation and loneliness, key catalysts of depression [60]. Keeping in regular contact and interacting with friends and family, joining social groups, and volunteering are all practical ways to keep others around oneself [10]. Finally, exposure to nature has been found effective to ease depression. Walking in nature, even parks and green spaces, has been shown to reduce risk factors such as rumination [14]. We next elaborate on the relationship between location-based mobile games and depression.

Location-based Mobile Gaming and Depression

Why might location-based mobile games ease the effects of depression? By integrating public health literature with research on how digital technology affects depression, we posit three means by which such games may impact depression: i) promoting outdoor physical activity, ii) facilitating face-to-face social interaction, and iii) increasing exposure to nature.

First, location-based mobile games encourage people to be physically active through gameplay, as players must physically move to play the game. Medical research indicates a strong relationship between physical activity (or exercise) and depression alleviation (e.g., [82, 86]). There are several reasons for this relationship. First, exercise promotes changes in the brain, including neural growth and reduced inflammation, while new activity patterns promote a feeling of calm and well-being [41]. Second, outdoor physical activity energizes people by releasing endorphins, which reduce perceptions of pain and stress [70]. Third, outdoor exercise can distract from daily routines, which helps break the negative thought cycles that feed depression [97]. This is beneficial because negative thoughts and feelings are less likely to manifest during physical activity. Applied to location-based mobile games like Pokémon Go, players who cover greater distances have opportunities to catch more Pokémon creatures, the key objective of the game, thus exercising more. Indeed, Althoff et al. [2] find that Pokémon Go players increased their physical activity by 1,473 steps a day (notably for sedentary populations), showing that location-based games do promote physical activity.

Second, in terms of face-to-face socialization, location-based mobile games create opportunities for people to socialize, build relationships, and enhance their sense of social belonging within the gaming community. Sung et al. [104] argue that games with offline social features encourage face-to-face interaction, communication, and self-disclosure, thereby limiting feelings of social isolation. Furthermore, research notes that the more people actively interact in person (i.e., communicating and sharing experiences), the less stress and anxiety they suffer [60]. Tateno et al. [107] support this by showing that young people who suffer from ineffectively treated social withdrawal leave their houses to play Pokémon Go. Finally, Cao [21] documents the benefits of socialization and finds that children with Asperger syndrome who played Pokémon Go become more sociable.

Third, location-based mobile games motivate people to go outdoors and be exposed to nature. Exposure to nature need not be deep in the wilderness and has generally been shown to have beneficial effects on depression alleviation. For instance, Bratman et al. [14] show that exposure to nature via a walk in public green spaces decreases rumination, a known risk factor for depression. Shanahan et al. [94] show that 30 minutes of walking in an urban

green space can reduce the prevalence of depression by up to 7 percent. These findings imply that access to nature in parks and green spaces may be vital to people's mental wellbeing, particularly in an increasingly urbanized world.¹² As Pokémon Go players must walk outdoors and explore their surroundings to capture Pokémon creatures, their exposure to nature intuitively increases, notably as the main game features (e.g., PokéStops¹³ and PokéGyms¹⁴) are often located at natural places (e.g., parks).

Importantly, these three mechanisms are not mutually exclusive and may even be mutually enhancing. If a large group explores a natural area with many Pokémon creatures, players in the same area are likely to join them. Such positive externalities increase physical activity, exposure to nature with the neighboring residents, and opportunities to socialize in person. Taken together, we argue that location-based mobile games may help to ease depression by encouraging healthy behavioral changes, specifically physical activity, faceto-face social interaction, and exposure to nature. While unlikely that non-medical interventions, such as exercise and socialization, would yield a material impact on severe forms of depression (e.g., major depressive disorder, bipolar disorder), the public health literature has made explicit reference to their positive effects in the case of lesser conditions of depression.

Data and Methodology

Data

To examine the effect of location-based mobile gaming on local depression trends, we leverage a unique empirical setup, the phased release of Pokémon Go into 166 regions,¹⁵ across 12 English-speaking countries, over 50 weeks between January 1, 2016, and December 12, 2016. This approach offers notable benefits. Pokémon Go is the most popular location-based mobile game in history, covering multiple countries and reaching 2.1 billion people. Furthermore, the game release is temporally and geographically staggered (Table 1), which allows us to execute a difference-in-differences estimation.

To measure the local depression trends, we leverage an increasingly popular approach from the medical and public health literature: internet search of depression-related terms [6, 7, 23, 56, 80, 108]. This well-established methodology gives us notable benefits, primarily that depression trends can be observed in real time across varying geographies.

	5	
English-Speaking Country (Area)	Continent	Release Date
Australia	Oceania	July 6
New Zealand	Oceania	July 6
United States	Americas	July 6
United Kingdom	Europe	July 14
Ireland	Europe	July 16
Canada	Americas	July 17
Puerto Rico	Americas	July 19
Philippines	Asia	August 6
Singapore	Asia	August 6
South Africa	Africa	October 4
India	Asia	December 13
Pakistan	Asia	December 13

Table 1. Release of Pokémon Go into 12 English-speaking countries/areas in 2016.

Note: English Speaking is defined by the CIA World Factbook based on either official language or state lingua franca.

For example, Tefft [108] shows a strong relationship between unemployment claims and search trends for "depression" and "anxiety." Similarly, Ayers et al. [6] show how depression-related search can be used to track economic and psychological distress (PD) in the population. Findings indicate that "PD queries [form] a framework and toolkit for real-time surveillance," giving clinicians and policymakers an impressive tool to monitor public health. In a systematic review, Nuti et al. [80] surveyed 70 studies between 2009-2013 that use Google Trends data in health care research, concluding that "Google Trends holds potential as a free and easily accessible means to access large population search data to derive meaningful insights about population behavior and its link to health and health care." A summary of mental health research using search data from the medicine, psychiatry, health economics, and public health literature is in Table A-2 of the Online Supplemental Appendix A.

Considering this information, it is worth noting that while conventional measurements for depression remain popular [11, 53, 76], they are concerning in our context. Namely, psychometric measurements are likely biased because they rely on self-reporting, which is problematic given the stigmatized nature of depression. Furthermore, health data from public administrations are limited in coverage and timeliness. For example, data from the CDC on mental health are collected and compiled on an annual basis. In contrast, the emerging availability of search query data offers solutions to the challenges posed by low frequent data entry [22, 29, 47], and has been embraced by information systems, medical, and population health researchers as a method to monitor and measure population-level trends of interest in a timely and unobtrusive fashion [6, 18, 45, 80].¹⁶

To capture the local depression trends, we extract internet search associated with depression at the region-week level from Google Trends. States outside the United States, hereafter also called regions, are defined as provinces or small countries (e.g., Wales in the United Kingdom). Weekly data are more stable than daily data, and using weekly data avoids the problem of missing values [101], as Google Trends does not provide data if there are insufficient searches at a location to break their internally defined privacy threshold. In line with extant work using Google Trends (e.g., [72]), we retrieve the search data following the approach described by Stephens-Davidowitz and Varian [99]. For each region, we pull a time series of depression-related search for the 50 weeks from January 1, 2016, to December 12, 2016. For each search term, we retrieve its time series at one time in the same request, instead of repetitive ones once a week.¹⁷ This ensures that search popularity values are scaled in the same way and are comparable within time series.¹⁸ In addition, we execute the data retrieval for all identified search terms (i.e., "stress," "anxiety," "depression," "fatigue") on the same day.¹⁹ We standardize (i.e., rescale to a mean of 0 and standard deviation of 1) each time series to ensure meaningful comparisons of relative changes across regions, which allows us to interpret changes in search, that is, flows, as opposed to levels of search, i.e., stocks.

We capture a full 50-week term in 2016 for two reasons. First, as Pokémon Go was initially released on July 6, 2016, we captured a full 6-month period before the release. This allows us to observe pre-treatment depression-related search trends for each region, which is critical for validating the parallel trends assumption of the difference-in-differences estimates [3, 12]. Varying the length of the pre-treatment period leads to similar results. Second, Pokémon Go was released to India and Pakistan on December 13, 2016, immediately after the conclusion of the sample.²⁰ Casting these two countries as untreated (i.e., Pokémon Go was not available) throughout the sample allows us to compare the depression-related search across treated and untreated regions over the entire period [3].

Before discussing our empirical approach, we note several potential limitations which might undermine our ability to capture the effect of Pokémon Go on local depression trends. First, depression-related search words from the Google Misery Index could be used by people who express sentiments versus those who suffer from clinically identified depression. While this is possible, we do not study and measure depression in a clinical context. Instead, we capture the widely accepted symptoms of depression that people discuss in their everyday lives, and that can be inferred from depression-related search trends. Second, it is difficult to tie the search of specific terms to depressed people, i.e., differentiating the general organic search of such terms by the public from searches by the depressed population. Yet, changes in organic search should not be affected by the introduction of Pokémon Go. Within-location change that is correlated with the release of the game is what our estimate captures, that is, change in behavior by people after Pokémon Go is released. Put simply, our empirical strategy does not intend to predict and explain all changes in depressionrelated search; only the difference in the differences in treated versus non-treated locations after the release of Pokémon Go. Third, it is worth considering whether our estimates capture search from Pokémon players versus from non-Pokémon players. This is a common limitation of studies using macro-level secondary data. Yet, for depressed persons who are not Pokémon players, there should be no change in their conditions of or trends in depression due to the release of Pokémon Go. The reason is that they do not play the game, and they are thus untreated by the game. In other words, there is no a priori reason to believe the changes of their overall search patterns would be different after the game release.

Measurement

Dependent Variable

Following extant work in public and population health (Table A-2 in the Online Supplemental Appendix A), the dependent variable for the main analysis is the Google Trends search popularity of depression-related terms for a region-week (Table 2) [6, 23, 56, 80, 108]. Raw depression-related search volume in Google Trends is measured on a scale from 0 to 100; 100 representing the greatest local search volume and zero the lowest. Hence, this is a relative measure, in the sense that each time unit for a specific search trend (e.g., "*anxiety*") is given a value relative to its peak in the search history, instead of a value relative to the search trends of other terms (e.g., "*fatigue*"). As discussed, we standardize the search

Variable	Data Source
Dependent Variable	
depression, stress, anxiety, fatigue	Google Trends Website, 2016
Independent Variable	
PokémonGo	Pokémon Go Wikipedia Page, 2016
Variables for Additional Analysis	
age (0-14; 15-64)	World Bank Data, 2016
gender	World Bank Data, 2016
GDP per capita PPP	World Bank Data, 2016
unemployment	World Bank Data, 2016
urbanization	World Bank Data, 2016
smartphone ownership	Newzoo's Global Mobile Report, 2017
mobile internet speed	Global State of Mobile Networks, 2017
past suicide rate (age standardized)	World Health Organization, 2015

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popularity of each term across regions over time for comparability. Following Ingraham's [56]²¹ *Google Misery Index*, we use "*depression*," "*stress*," "*anxiety*," and "*fatigue*" to capture variation in local depression.

One concern with this approach is that using a single term in any given regression analysis as a proxy for overall depression may introduce measurement error. For example, someone may search "*fatigue*" immediately after exercising. To mitigate this concern, we construct a composite index to measure depression using a Principal Component Analysis (PCA). PCA is an unsupervised machine learning method used to generate a set of representative components (or factors) that capture most of the variability in a set of variables with an orthogonal transformation [57]. We employ a PCA so that the common variance of all depression-related terms is summarized by the principal component, from which we can approximate the aggregate level of depression-related search more effectively than using the variance of any single search term. For a detailed discussion of the PCA, see the Online Supplemental Appendix B.

Independent Variables

Our main independent variable is a dichotomous indicator PokémonGo. This variable is set to one if Pokémon Go had been introduced to region j at week t; zero otherwise. This indicator captures the change in depression-related search in regions that have received the PokémonGo treatment, as compared to those regions that have yet to receive the PokémonGo treatment as of week t.

In falsification tests, we use Pokémon-related search intensity, as well as local Pokémon Go game features to proxy gameplay, as opposed to the mere availability of the game. In these estimations, we use both a set of search terms (viz. "*Pokémon near me*," "*where to catch Pokémon*," "*PokéStop*," and "*PokéGym*," Column 2 in Table C-8 in Online Supplemental Appendix C) as well as the number of PokéStops and PokéGyms (i.e., critical game elements) in U.S. cities (Table C-10A). Using the number of PokéStops and PokéGyms as independent variables enables the validation and replication of the main analysis by varying the measure for Pokémon Go availability. Results remain consistent.

Control Variables

We first account for time-invariant region-level heterogeneity using location fixed effects. For locations outside the United States, this is done using "province" or "region" fixed effects. Inside the United States, they are state fixed effects. These fixed effects capture time-invariant region-level factors (e.g., public health service conditions, mobile internet development) throughout the course of the sample that may be correlated with both the release of Pokémon Go and local search of depression-related terms. For example, demographic (e.g., age or gender composition) or social-economic conditions of a region are relatively stable across weeks and are thus captured by the region fixed effect.²² Second, we include time fixed effects at the week level to control seasonal or temporal changes in depression-related search. Finally, we include country-specific linear and quadratic time trends to account for time-varying confounders that follow different trajectories within each location.²³ For example, the release of Pokémon Go might be correlated with depression-related seasonal confounds, for example, seasonal affective disorder, stemming from the summertime

		N	Mean	Std. Dev	Min	Max
Variable	Measurement	(1)	(2)	(3)	(4)	(5)
depression	Search intensity of term "depression"	7,900	49.320	26.550	0	100.00
stress	Search intensity of term "stress"	7,950	53.210	25.890	0	100.00
anxiety	Search intensity of term "anxiety"	7,850	53.140	27.490	0	100.00
fatigue	Search intensity of term "fatigue"	7,200	48.110	26.740	0	100.00
PokémonGo	=1 if released at the region <i>j</i> and week <i>t</i>	8,300	0.329	0.470	0	1.00
age (0-14)	Age from 0 to 14 (percent of total population)	8,300	0.240	0.060	0.16	0.35
age (15-64)	Age from 14 to 64 (percent of total population)	8,300	0.660	0.020	0.60	0.73
gender	Female (percent of total population)	8,300	0.500	0.010	0.48	0.52
GDP per capita PPP	GDP per Capita PPP, current international \$	8,300	9.980	1.000	8.52	11.35
unemployment	percent of total labor force	8,300	0.061	0.050	0.02	0.26
urbanization	Urban population (percent of total population)	8,300	0.650	0.230	0.33	1.00
smartphone ownership	Smartphone users (percent of total population)	8,300	0.490	0.260	0	0.77
mobile internet speed	Megabits per second	8,300	0.113	0.0700	0.03	0.30
past suicide rate	Suicides per 100,000 people per year	8,300	0.120	0.04	0.03	0.16

Table 3. Variables, measurement, and summary statistics

Notes: Country-level variables (e.g., urbanization, smartphone ownership, mobile internet speed) are shown here but not included in the main analysis as they are time-invariant within each country and absorbed by the region fixed effects. But we use them to check exogeneity of the game release (Table C-7 in the Online Supplemental Appendix C) and explore treatment effect heterogeneity across countries (Table C-9).

release of the game in the United States.²⁴ Using the location-specific time trends as well as time fixed effects should capture any systemic issues stemming from this launch timing.²⁵ Tables 2 and 3 provide data sources, measures, and summary statistics.

Empirical Strategy

Our empirical strategy relies on the phased rollout of Pokémon Go into 166 regions across 12 English-speaking countries in 2016 using a difference-in-differences approach. This is performed by comparing the change in depression-related search, before and after the release of the game, to change in depression-related search in regions where the game has yet to be released. This approach has two benefits. First, the phased release creates a natural control group, i.e., those regions yet to receive the *PokémonGo* treatment. Second, it eliminates concerns of aggregation biases in the analysis of regions, rather than individuals [74]. We model depression-related search (y_{jt}) in region j at week t using the following specification:

$$y_{it} = \gamma_i + \lambda_t + \beta_1 PokemonGo_{it} + \varepsilon_{it}$$
(1)

PokemonGo_{jt} indicates whether the game has been activated in region *j* as of week *t* (1 if yes, 0 otherwise). γ_j represents the vector of region fixed effects, and λ_t represents the vector of week fixed effects. β_1 is the coefficient of interest. A negative β_1 indicates that the introduction of Pokémon Go is associated with a decrease in depression-related search. The estimator is an OLS with robust standard errors clustered at the country level.

Results

Table 4 presents the results using searches for "*depression*," "*stress*," "*anxiety*," and "*fatigue*" as dependent variables. Conditional on region and week fixed effects, we find that the release of Pokémon Go is associated with a decrease in search for "*depression*," "*stress*," and

Independent Variable:	depression	stress	anxiety	fatigue	PCA (depression, stress, anxiety, fatigue)
PokémonGo	(1)	(2)	(3)	(4)	(5)
(i) Region & Week Fixed-Effects (FE)	-0.417**	-0.100	0.059	-0.086	-0.344**
	(0.149)	(0.177)	(0.040)	(0.080)	(0.155)
(ii) FE + Linear Time Trends	-0.585***	-0.650***	-0.013	0.009	-0.427**
	(0.175)	(0.167)	(0.072)	(0.093)	(0.209)
(iii) FE + Quadratic Time Trends	-0.318**	-0.479***	0.080	-0.075	-0.365**
	(0.143)	(0.117)	(0.047)	(0.051)	(0.166)

Table 4. Effects of Pokémon Go release on depression-related search.

Note: Robustness standard error (clustered at the country level) in parentheses. ***p < 0.01. * p < 0.05. *p < 0.1.

"*fatigue*." However, only the *depression* term is significant at conventional levels (Row (*i*)). Row (*ii*) adds country-specific linear time trends ($\theta_i t$), and Row (*iii*) incorporates quadratic time trends ($\delta_i t^2$) to account for the idiosyncratic trend for each country. Results remain consistent, indicating that, on the margin, the release of Pokémon Go decreases the search interest in *depression* and *stress*, conditional on fixed effects, as well as location-specific time trends. We observe no evidence of an effect on search intensity related to *anxiety* or *fatigue*. However, this may be due to the commonality of the terms. We, therefore, take the described PCA approach to construct a composite depression index using the first principal component for the variance of [*depression*, *stress*, *anxiety*, *fatigue*]. We then replicate the estimation of Eq. 1 using the composite depression index as the dependent variable.²⁶ Results in Column 5 of Table 4 indicate a significant decrease in the aggregate depression-related search after the release of Pokémon Go across all specifications [56].²⁷

Testing the Parallel Trend Assumption

While the results of the baseline difference-in-differences estimations are compelling, it is important to note that they are subject to several assumptions. The most important one is the absence of heterogeneity in the pre-treatment trends, that is, the difference-in-differences assumes depression-related search before the release of Pokémon Go is parallel across both the treated and untreated regions [3, 12]. This assumption may not be satisfied if unobservable environmental factors, which are native to individual regions, result in pre-treatment heterogeneity. For example, if Pokémon Go was released in countries that happened to launch a program aimed at reducing the cost of mental healthcare, there might be additional search and treatment seeking prior to the game release. To rule out this possibility, and further substantiate the claim that the release of Pokémon Go can be treated as an exogenous event conditional upon controls (i.e., fixed effects and location-specific time trends), we execute a variant of Autor's [5] leads and lags model [19, 24]. In doing so, we include pre- and post-treatment dummies to capture the inter-temporal effects of the game release. Formally:

$$y_{jt} = \gamma_j + \lambda_t + \sum_k \tau_k PrePokemonGo_{jt}(k) + \beta PokemonGO_{jt} + \sum_m \omega_m PostPokemonGo_{jt}(m) + \varepsilon_{jt}$$
(2)

*PrePokemonGo*_{jt}(k) is an indicator equal to 1 if the temporal distance between the game release into region j and the pre-treatment week t is k weeks, while *PostPokemonGo*_{jt}(m) is an indicator equal to 1 if the temporal distance between the game release into region j and the post-treatment week t is m weeks. Intuitively, this model allows us to capture trends semi-parametrically, and to observe the effects week-by-week before and after the *PokémonGo* treatment. Consistent with extant literature, we use the week prior to the release of Pokémon Go as the baseline by normalizing the coefficient of *PrePokemonGo*_{jt}(-1) to zero [19]. Weeks later (or earlier) than eight weeks after (or before) Pokémon Go entry are collapsed into a single dummy to increase interpretability. Results are in Table 5 and Figure 1.

Table 5 shows small differences in the pre-treatment period, except for a single point estimate six weeks prior to the game release, between treated and untreated regions (i.e., coefficients of *PrePokemonGo_{it}(k)*, for k < -8 to k < -1, are not significant). Point estimates

Dependent Variable: PCA (depression, stress, anxiety, fatiaue)	(1)	(2)	(3)
	0.110	0.001	0 122
2 8 weeks until the Pokemon Go release	0.118	0.081	0.133
7 wooks until the Pokémon Co release	(0.150)	(0.120)	(0.111)
7 weeks until the Fokemon do release	(0.032	(0.043	(0.063)
6 weeks until the Pokémon Go release	(0.074)	0.10//**	0.003)
o weeks until the Fokemon do release	(0.087)	(0.073)	(0.070)
5 weeks until the Pokémon Go release	-0 113	-0.105	-0.034
5 weeks until the Fokemon do release	(0.081)	(0.079)	(0.080)
4 weeks until the Pokémon Go release	0.067	0.078	0 146*
+ weeks until the Fokemon Go release	(0 129)	(0.093)	(0.077)
3 weeks until the Pokémon Go release	-0.056	-0.041	0.018
s weeks and the rokemon of recuse	(0.126)	(0.107)	(0.101)
2 weeks until the Pokémon Go release	-0.041	-0.014	0.049
	(0.101)	(0.075)	(0.069)
1 week until the Pokémon Go release		Omitted Baseline	(******)
0 week since the Pokémon Go release	-0.266**	-0 228**	-0 177**
o week since the rokemon do release	(0.088)	(0.075)	(0.070)
1 week since the Pokémon Go release	-0 298***	-0.257***	-0 219***
Tweek since the Fokemon do release	(0.092)	(0.059)	(0.053)
2 weeks since the Pokémon Go release	-0.225**	-0.177**	-0.141*
	(0.082)	(0.069)	(0.077)
3 weeks since the Pokémon Go release	-0.120	-0.060	-0.040
	(0.092)	(0.092)	(0.101)
4 weeks since the Pokémon Go release	-0.189**	-0.127	-0.120
	(0.084)	(0.078)	(0.089)
5 weeks since the Pokémon Go release	-0.234**	-0.163	-0.160
	(0.091)	(0.105)	(0.118)
6 weeks since the Pokémon Go release	-0.285**	-0.202	-0.217
	(0.122)	(0.126)	(0.152)
7 weeks since the Pokémon Go release	-0.118	-0.031	-0.053
	(0.113)	(0.098)	(0.105)
≥ 8 weeks since the Pokémon Go release	-0.030	0.117	-0.012
	(0.106)	(0.152)	(0.129)
Region FE	YES	YES	YES
Week FE	YES	YES	YES
Linear Time Trends	NO	YES	YES
Quadratic Time Trends	NO	NO	YES
# Observations	7,007	7,007	7,007
# Region	143	143	143
Adjusted R-squared	0.135	0.234	0.263

Table 5. Relative time model of Pokémon Go release on depression-related search.

Note: Robust standard errors (clustered at the country level) in parentheses. ***p < 0.01. **p < 0.05. *p < 0.1.

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Figure 1. Effects of Pokémon Go release on depression-related search, over time. *Note*: Figure 1 visualizes the estimates in Column 1 of Table 5. Solid line depicts the difference in depression-related search between treated and untreated regions over time, while dash lines the upper and lower bounds of 95 confidence intervals.

vacillate intermittently above and below zero, suggesting no systemic heterogeneity in the pre-treatment period. This lends credence to the notion that the estimations do not violate the parallel trends assumption [3]. Moreover, when examining the post-treatment coefficients, we observe a significant decrease (p < 0.05) in depression-related search immediately after the introduction of Pokémon Go, and the negative effect holds for several weeks. Interestingly, the effect appears to dissipate after about six weeks or so, suggesting that it is not permanent. This is not surprising. A short-term reduction in search is consistent with the herd behavior of playing the game [103], which had peak popularity lasting just under two months. While long-term players did persist in playing, most players stopped their play in the months following initiation, thereby resulting in a diminished herding effect. Furthermore, it is consistent with evidence from medicine, inasmuch as the treatment's benefits will fade when the treatment is removed. Thus, like any short-term treatment, the symptoms of depression returned when the treatment was abandoned. Figure 1 further shows the effect and corroborates the absence of a pre-treatment trend. In sum, these results provide evidence that the introduction of Pokémon Go decreases depression-related search in the short term.

Enhancing Depression Measurement

One empirical challenge lies in the fact that depression-related search may not fully capture the local incidence rate of depression. Prior studies using search query data acknowledge this challenge and propose several solutions to assess the comprehensiveness of the selected terms and the accuracy of predicting offline trends using Google Trends data [18, 22, 29, 45, 48, 99, 101]. Inherent in this challenge are two core issues: proper selection of search terms

to capture changes in offline depression (recall that the terms we leverage are based on the widely used Google Misery Index) and a strong correlation between depression-related search and objective, and previously corroborated, measures of local depression.

To ensure that the pool of selected search terms is appropriate, we examine their validity using Brynjolfsson et al. [18]'s "Crowd-Squared" approach. In doing so, we conduct a word association task on Amazon Mechanical Turk wherein we ask participants to "Write 5 terms that come to mind when seeing the word *depression* (a mental disorder)." Demographic information of the participants is in Table D-1 in the Online Supplemental Appendix D. For any term frequently reported by more than 1 percent of respondents, we collect weekly search data from Google Trends. We then replicate our estimations using these newly identified terms (viz., "*unhappy*," "*tired*," "*sad*," "*lonely*," "*hopeless*," "*dark*," "*crying*," "*blue*"). Results in Table 6 show that the Pokémon Go release is negatively associated with the newly identified depression-related search (Columns 1-8), corroborating the main effect in Table 4. Results are consistent when the PCA-generated composite depression measure is used (Column 9).

Next, we examine if there is a significant difference between the point estimates of the original search terms (i.e., Google Misery Index) and the terms obtained using the Brynjolfsson et al. [18] method. In doing so, we regress different composite depression measures on the introduction of Pokémon Go (Columns 1-3 in Table 7) and compare the coefficients directly. These measures include those from the PCA of the original four terms, the eight newly identified terms, and the comprehensive set of twelve terms. Results show that adding search terms does not significantly affect the estimates, notably when location-specific time trends are considered (Columns 4-6). This suggests that the observed effect of Pokémon Go on local depression using Google Misery terms is robust to different data selection methods.

To resolve the second concern, i.e., the face validity of using internet search trends to measure depression, we correlate depression-related search from Google Trends and objective mental health measures from two well-established administrative datasets: the GHDx and the CDC's Behavioral Risk Factors Surveillance Systems (BRFSS) survey. We avoid using these data to measure the dependent variable in our main analysis for structural reasons. In short, because these data are collected at the country-year and state-month level, they lack the granularity and sensitivity to capture short-term changes in depression once Pokémon Go was released, as Google Trends can. GHDx captures the number of new mental disorder cases per

Table 6. Effects of Pokémon Go release on depression-related search (search terms generated using "crowd-squared" approach).

Independent Variable:	lonely	unhappy	sad	hopeless	dark	crying	tired	blue	PCA (all terms)
PokémonGo	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(i) Region & Week FE	-0.0374	-0.118***	-0.365***	-0.0112	-0.415***	-0.264**	-0.019	-0.154	-0.448***
	(0.0628)	(0.0215)	(0.113)	(0.0478)	(0.130)	(0.0978)	(0.059)	(0.321)	(0.122)
(ii) + Linear Trends	-0.0573	-0.279***	-0.512**	-0.000531	-0.392*	-0.229	0.041	0.523**	-0.334**
	(0.0337)	(0.0602)	(0.222)	(0.0426)	(0.184)	(0.136)	(0.113)	(0.231)	(0.123)
(iii) + Quadratic Trends	-0.0837	-0.120*	-0.511***	-0.0142	-0.359	-0.291**	-0.001	0.308	-0.383**
	(0.0961)	(0.0597)	(0.145)	(0.0608)	(0.236)	(0.120)	(0.102)	(0.224)	(0.125)

Note: Robust standard errors (clustered at the country level) in parentheses. ***p < 0.01. * p < 0.05. *p < 0.1.

		DV: Composite Depression Using Different Sets of Sea	Differences Between Coefficients (t-Statistics)			
Independent Variable:	PCA (depression, anxiety, stress, fatigue)	PCA (unhappy, tired, sad, lonely, hopeless, dark, crying, blue)	PCA (depression, anxiety, stress, fatigue, unhappy, tired, sad, lonely, hopeless, dark, crying, blue)	(2)-(1)	(3)-(2)	(3)-(1)
PokémonGo	(1)	(2)	(3)	(4)	(5)	(6)
(i) Region &	-0.197***	-0.448***	-0.366***	-1.825*	-2.134**	0.627
Week FE (ii) FE + Linear	(0.0635) -0.353** (0.0830)	(0.122) -0.334** (0.123)	(0.0473) -0.396*** (0.0752)	0.128	-0.384	-0.430
i rends (iii) FE + Quadratic Trends	-0.298** (0.0798)	-0.383** (0.125)	-0.410*** (0.0845)	-0.573	-0.964	-0.179

Table 7.	Effects	of the	Pokémon	Go	release	on	depression-related	search	using	different	composite
depression	on meas	ures									

Note: Robust standard errors (clustered at the country level) in parentheses. ***p < 0.01. **p < 0.05. *p < 0.1.

100,000 people between 2004 and 2016 for a given country. The BRFSS, which is the United States only, captures each survey response on mental health status, that is, the percentage of days in the past 30 days with poor mental health conditions, and it aggregates the microdata to each month (2004-2016) for each of the 50 States and Washington DC. Although these measures do not exclusively capture depression, they should provide a reasonable facsimile of offline trends in population mental health, of which depression is the most prevalent, over time. To determine the correlation between depression-related search trends and offline mental health trends, we regress the latter on the PCA-generated composite depression index that integrates multiple depression-related search trends.

Results are in Column 1 of Table 8 and indicate a positive and statistically significant correlation at both the country-year and state-month levels. In addition, we consider the newly-identified search terms using the "Crowd-Squared" approach [18], and the estimates remain consistent (Column 2). In sum, the positive and significant correlation suggests that the depression-related search well captures the local trends in mental health conditions.²⁸

Robustness and Heterogeneity

While the results hold across several specifications and consistently support the notion that the introduction of Pokémon Go is associated with a decrease in depression-related search, alternative explanations of this relationship exist. We thus extend our empirical analysis to ensure the robustness of the observed effect (see the full list of tests in Table 9). Among these falsification analyses, we consider and rule out the influences of seasonality in Google search trends (Table C-1 in the Online Supplemental Appendix C), organic changes in the general Google search (Table C-2), and different language use preferences across various English-speaking countries (Tables C-3A and C-3B). We add population weighting to account for heteroskedasticity, heterogeneity, and potential sampling issues (Table C-4). We check the possibility of serial correlation using randomly-generated hypothetical release dates of Pokémon Go as placebo treatments (Table C-5). We conduct falsification tests using non-communicable diseases

		Predictors				
		PCA				
Datasets /		PCA (depression, anxiety, stress, fatigue)	(depression, anxiety, stress, fatigue, unhappy, tired, sad, lonely, hopeless, dark, crying, blue)			
Unit of Analysis	Dependent Variables	(1)	(2)			
GHDx data /	Mental health	306.0084***	200.2708***			
Country-Year	incidence rate (# new cases/100k in a given year)	(46.4345)	(36.0494)			
BRFSS Data /State- Month	Percentage of Days with poor mental health conditions in the past 30 days	0.0012*** (0.0002)	0.0010*** (0.0002)			

 Table 8. Correlation between depression-related search using Google trends data and depression trends using health administrative data.

Note: GHDx stands for Global Health Data Exchange dataset. BRFSS stands for Behavioral Risk Factor Surveillance System dataset. Different depression measures are used based on GHDx and BRFSS data, respectively. Columns 1-2 report the coefficients on PCA (search terms) when running linear regressions of mental health conditions (using administrative mental health measures) on depression-related search popularity. The coefficients do not change much even if time dummies are added. ***p < 0.01. **p < 0.05. *p < 0.1.

(Table C-6), test the potential reverse causality in the game release (Table C-7), and compare the effect of game availability with that of gameplay (Table C-8). In addition, we explore heterogeneity in the observed effect across countries (Table C-9) and alter our sampling strategy by zooming in and examining the Pokémon Go effect across U.S. cities and states (Tables C-10A and C-10B). These results remain consistent with the main estimators (Column 5 of Table 4).

Exploring Underlying Mechanisms

Having established compelling evidence for the decline in depression-related search after the release of Pokémon Go, we explore the underlying mechanisms that might drive the effect. As discussed, location-based mobile games encourage outdoor physical activity, faceto-face socialization, and interaction with nature, all of which may help alleviate the symptoms of depression [14, 32, 60]. To empirically test these mechanisms, we take three approaches. First, we use search data to capture behavioral changes after the introduction of Pokémon Go. As the relationship between positive behavioral changes (e.g., physical activity) and depression has been well established in the public health literature, it is intuitive that we might be able to explain the changes in behavior by examining changes in the related search (much as we did with depression-related search). Next, as the first approach does not allow us to test each mechanism simultaneously, we proxy each to capture the extent of change in the mechanism (i.e., physical activity, socialization, and exposure to nature). In doing so, we examine how these factors moderate the effect. Note that this is impossible with the first approach due to multicollinearity. Finally, to disentangle confounding mechanisms (e.g., distraction), we use a digital game with similar gameplay as Pokémon Go, albeit without the aforementioned mechanisms.

To execute the first approach, our objective is to find search trends that reflect different behavioral mechanisms by which Pokémon Go might affect depression-related search. In doing so, we use Brynjolfsson et al. [18]'s "Crowd-Squared" approach again to obtain a representative set for each of these behavioral mechanisms.

Challenges	Tests	Results	Location
Measurement	(i) Use multiple depression-related terms based on "Google Misery Index" to measure depression	A significant decrease in the search of "depression" after the game release	Table 4
	(ii) Provide a mathematical proof that comparing to individual search terms, using the PCA-generated composite measure will better approximate the true local depression trends	Results remain consistent and even more significant if PCA-generated composite depression index is used	Appendix B
	(iii) Expand the list of search terms using the "Crowd-Squared" approach, i.e., crowdsourcing terms from Amazon Mechanical Turkers on what they would search online if they feel depressed	Results remain consistent when newly identified search terms from "Crowd- Squared" approach are used	Table 6 Table 7 Appendix D
	 (iv) Test the correlation between offline depression trends using administrative health data and online depression-related search using Google Trends data 	Correlation is significantly large, indicating depression-related search well capture the local depression trends	Table 8
	(v) Account for different language use by allowing distinct "depression" terms as DV for each country	Results remain consistent	Tables C-3A and C-3B
	(vi) Replicate the main analysis using the administrative measure of mental health as DV	Effect remains consistent. Offline average mental health conditions decrease after the Pokémon Go release.	Table C-10B
ls the control group a good counterfactual?	Test a relative time model with leads and lags of Pokémon Go entry	No heterogeneity in depression-related search in the pre-treatment trends; the parallel trend assumption is valid	Table 5 Figure 1
Seasonal confounders?	Conduct a placebo test: Effects of <i>Placebo</i> Pokémon Go activation (as if it would have been released in 2015) on depression-related search in 2015 (actual release was in 2016)	The identified effect is not driven by seasonal confounders	Table C-1
A continued decrease in general search on Google?	Test the effect of Pokémon Go release on general terms, including "news," "translation," "maps," "weather," "calculator"	The decline of depression-related search is not driven by the general downward search trends on Google	Table C-2
Heteroskedasticity, heterogeneity, sampling issue?	Run regression weighted by regional population	Results remain consistent	Table C-4
Spurious correlation?	(i) Check spurious and serial correlation using hypothetical release dates of Pokémon Go release	No spurious and autocorrelation	Table C-5
	(ii) Test the effects of Pokémon Go on non-communicable diseases	No spurious correlation	Table C-6
Reverse causality?	Run a hazard regression predicting Pokémon Go release using depression-related search lagged 1, 2, 3 weeks, and other country-level covariates	Past depression-related search trends do not predict Pokémon Go release; reverse causality is not a big concern	Table C-7
Availability versus actual gameplay	Test the effects of Pokémon-related search on depression-related search	The actual gameplay of Pokémon Go, instead of mere availability, may explain the observed effect	Table C-8
Heterogeneity across countries?	Estimate the heterogeneous effects of Pokémon Go (i.e., smartphone ownership, mobile internet speed, urbanization) across countries	The effect is more pronounced in areas with high smartphone penetration, mobile speed, and urbanization	Table C-9
Generalizable?	Replicate the main analysis using U.S. data on the MSA-week and state- month level, respectively	Results remain consistent	Table C-10A

Table 9. Summary of empirical challenges, tests, and results.

(Continued)

Challenges	Tests	Results	Location
Exploring underlying mechanisms	 (i) Test the effects of Pokémon Go release on the search trends related to outdoor physical activities, offline socialization, and exposure to nature 	Theoretical mechanisms are supported by a significant increase in the trends related to behavior changes followed by the release of Pokémon Go	Table 10
	 (ii) Test the channeling effects of behavioral mechanisms on the effect of Pokémon Go release on depression- related search 	Moderation effects of behavioral change proxies are significant	Table 11
	(iii) Test the effects of Pokémon Sun and Moon release on the depression- related search trends (to check the alternative explanation in terms of distraction)	This game has similar gameplay and distraction with Pokémon Go, but no incentives for positive behavior changes. Results show such a game does not—and even increase— depression-related search	Table 12

Table 9. (Continued).

Table 10. Effects of Pokémon Go release on searches related to physical activity, face-to-face socialization, and exposure to nature.

	Physical Activity	Face-to-face Socialization	Exposure to Nature
Independent Variable:	DV: PCA (running, hiking, jogging, biking, swimming, trail, yoga, outside)	DV: PCA (fun, restaurant, party, laughing, dinner, eating, conversation, places)	DV: PCA (hiking, trail, park, animal, places, forest, meditation, green, environment)
PokémonGo	(1)	(2)	(3)
(i) Region & Week Fixed Effects (FE)	0.488**	0.524**	0.707**
	(0.188)	(0.261)	(0.300)
(ii) FE + Linear Time Trends	1.068***	0.665***	1.325**
	(0.268)	(0.211)	(0.494)
(iii) FE + Quadratic Time Trends	0.727***	1.025***	0.854**
	(0.206)	(0.234)	(0.343)

Note: Robust standard errors (clustered at the country level) in parentheses. ***p < 0.01. ** p< 0.05. *p < 0.1.

We recruited 500 participants on Amazon Mechanical Turk to associate words with physical activity, offline socialization, and exposure to nature, and list their preferred search terms. After crowdsourcing the terms, we use those which appear in more than 1 percent of responses.²⁹ We then replicate Equation 1 with the PCA-generated composite indexes of these search terms as the dependent variables. Results are in Table 10 and indicate a strong relationship between these searches and the release of Pokémon Go. This finding lends credence to the anecdotal claims that location-based mobile games encourage positive behavioral changes.

Second, we examine the channeling impact of behavioral changes on depression-related trends (i.e., whether the behavioral changes moderate the effect of Pokémon Go). In doing so, we use the average obesity rate, population density, and search interest in parks one year before the release of Pokémon Go as proxies for the extent of physical inactivity, offline socialization, and willingness to interact with nature at the country level.³⁰ We then replicate our estimations. Results are in Table 11, indicating that the identified effect of Pokémon Go

	DV: PCA (depression, stress, anxiety, fatigue)				
	(1)	(2)	(3)	(4)	(5)
PokémonGo	-0.365**	0.281	-0.415**	0.240	0.418
	(0.166)	(0.378)	(0.160)	(0.501)	(0.520)
PokémonGo $ imes$ Obesity Rate		-0.0255**			-0.0243*
		(0.00980)			(0.0135)
PokémonGo $ imes$ Population Density			0.000235***		0.000172**
			(0.0000722)		(0.0000561)
PokémonGo × Park				-0.00968*	-0.00729*
				(0.00549)	(0.00417)
Region FE	YES	YES	YES	YES	YES
Week FE	YES	YES	YES	YES	YES
Linear Time Trends	YES	YES	YES	YES	YES
Quadratic Time Trends	YES	YES	YES	YES	YES
# Observations	7,150	7,150	7,150	7,150	7,150
# Regions	143	143	143	143	143
Adjusted R-squared	0.253	0.255	0.254	0.254	0.256

Table 11. Moderating roles of physical activity, face-to-face socialization, and exposure to nature on the effects of Pokémon Go release on depression-related search.

Note: Obesity rate (percent) is the proportion of the population that is obese. The data is from *The World Factbook* by Central Intelligence Agency in 2016. *Population density* (people per sq. kilometers) is from World Bank data in 2016. *Park* is the average search interest of "park" on Google in 2015 (one year before the release of Pokémon Go), which represents a population's willingness to access public green space. These three measures are proxies of physical inactivity, offline socialization, and exposure to nature. Robust standard errors (clustered at the country level) in parentheses. ***p < 0.01. **p < 0.05. *p < 0.1.

Table 12. Falsification test for alternative mechanisms: Effects of Pokémon sun and moon release on depression-related search.

Independent Variable: PokémonSun&Moon	depression	stress	anxiety	fatigue	PCA (depression, stress, anxiety, fatigue)
(=1 if released, 0 otherwise)	(1)	(2)	(3)	(4)	(5)
(i) Region & Week Fixed-Effects (FE)	0.369**	0.494***	0.0360	-0.372***	0.414**
	(0.157)	(0.126)	(0.0782)	(0.0883)	(0.149)
(ii) FE + Linear Time Trends	1.389***	1.437***	0.557**	0.241	1.180***
	(0.0887)	(0.285)	(0.245)	(0.276)	(0.319)
(iii) FE + Quadratic Time Trends	0.743***	0.710**	0.507**	0.315	0.700**
	(0.182)	(0.279)	(0.191)	(0.291)	(0.228)

Note: Robust standard errors (clustered at the country level) in parentheses. ***p < 0.01. **p < 0.05. *p < 0.1.

on depression search is larger at locations where people remain at a relatively low level of physical activity (e.g., high obesity rate), have less opportunity to socialize offline (e.g., low population density), and they are more willing to interact with parks or green spaces. In other words, the game influences depression-related search to a greater extent where behavioral changes are most needed. This further corroborates the channeling from location-based mobile gaming to local depression trends through behavioral mechanisms.

Finally, while the aforementioned approaches provide suggestive evidence of the behavioral mechanisms, it is possible that alternative mechanisms may be at play. For example, Pokémon Go may simply be a short-term distraction like any other game. We, therefore, conduct a falsification test using a video game, Pokémon Sun and Moon, which has gameplay similar to Pokémon Go. The properties of Pokémon Sun and Moon allow us to check whether distraction confounds our explanation and to examine the effects of different game features (Pokémon Sun and Moon not being location-based). Put simply, while Pokémon Sun and Moon has similar gameplay to attract players, it does not encourage outdoor exercise or exposure to nature because there is no location-based component to the game. However, it does retain the game's social features (e.g., battling with friends, trading Pokémon objects), albeit not face to face. Importantly, Pokémon Sun and Moon had a similar phased release as Pokémon Go did because it was gradually released to North America, Australia, and Europe in later 2016 at different weeks. Results are in Table 12 and, interestingly, show a significant *increase* in depression-related search following the release of Pokémon Sun and Moon. In contrast to the Pokémon Go effect, this result provides suggestive evidence that digital games without location-based features encouraging outdoor activities and offline socialization may not yield similar effects on local depression trends.

Discussion

Key Findings

In this study, we investigate the relationship between location-based mobile gaming and local depression trends. Building on burgeoning work in information systems and public health [17, 18, 29, 45, 47, 48, 80, 108], we exploit the phased rollout of Pokémon Go into 166 regions of 12 English-speaking countries using internet search data. Results indicate a material decline in the search associated with depression, following the release of Pokémon Go. These findings suggest that location-based mobile gaming may yield short-term relief of an acute and mild form of depression. Empirical evidence also suggests the behavioral mechanisms underpinning this observed effect, notably that Pokémon Go has its observed effects by encouraging outdoor physical activity, face-to-face social interaction, and exposure to nature.

Before discussing implications for theory and practice, we make one important caveat. It would be inappropriate to conclude from this study that location-based mobile games like Pokémon Go can immediately be deployed on a large scale as a quick remedy to depression, particularly severe or clinical depression, or serve as a substitute for medical treatments. Indeed, our study of self-harm related search (Table B-6 in Appendix B) indicates a clear boundary to the effect. Instead, we hope this work serves as a call for future research in three key directions. First, we believe it is important for medical practitioners to assess individuallevel effects of location-based mobile gaming, as opposed to the population-level effects we measure. Second, we encourage future research to explore factors that might push the identified short-term effect into a long-term effect. While the planned obsolescence of video games makes the identification of "critical success factors" appealing, ensuring positive behavioral changes that persist across successive generations of games will be critical. Third, we hope this work serves as a call for more in-depth and rigorous research on the complementarities between location-based mobile gaming, as a non-medical approach to depression treatment, and medical interventions alleviating the symptoms of depression in clinical settings. As the medical system is already overloaded, and the coupling of proactive behavioral interventions is often beneficial, we believe that location-based mobile gaming can improve patient welfare by complementing clinical remedies.

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Contributions and Implications for Theory and Research

This study makes several contributions with implications for theory and research. First, we examine an emerging technological artifact, location-based mobile games, and their potential effects on public health. While IS literature has identified numerous negative effects of technology on public health (e.g., technostress in the workplace [9], increased local rates of suicide [59]), we observe a positive effect of location-based mobile games on depressionrelated search. This suggests that this technological artifact may facilitate positive behavioral changes, namely physical activity, face-to-face socialization, and interaction with nature, which provides a nuanced contribution to the nascent IS literature on digital gaming [66]. Indeed, while research in this space has examined both means by which gaming can be less addictive [52] and incorporated into the workplace [102], it has yet to consider the potential of location-based gaming in the context of alleviating depression (at least in its mild forms). Furthermore, our findings enrich the discussion of the social effects of digital gaming, especially for location-based mobile games that facilitate online to offline socialization [39, 42]. Finally, this work contributes to the literature on the broader societal impacts of IT on public health (e.g., [24, 44, 50, 67, 84]) by exploring the potential mental health benefits from digital gaming.

Second, this work contributes to the emerging literature on public and population health by illustrating the potential for location-based mobile games to combat local depression. While existing research has extensively discussed medical interventions [30, 65, 71, 81], we believe a similar focus on non-medical and behavioral approaches is warranted, as they are often less costly and may be effective in coping with public health problems, such as outdoor activity for obesity. While our findings require corroboration from medical professionals to identify individual-level effects in clinical settings, we believe it is a first step in drawing the attention of scholars and practitioners to technology-based behavioral interventions. The critical takeaway is that location-based mobile gaming may be effective in encouraging people toward positive behavioral changes. Thus, our study responds to the calls of incorporating "Serious Games [75]," that is, video games with an applied positive purpose, for better clinical practices of mental health care.

Finally, this study makes an empirical contribution, particularly by measuring local depression trends using non-traditional data, namely, depression-related internet search using Google Trends. While this approach has been taken by dozens of scholars in the medical field (See Appendix A in the Online Supplemental Material), it has yet to be fully embraced by the IS community. We employ this approach due to a major challenge in mental and public health research, how to assess local depression trends among a population that cannot be reached with surveys [7]. Internet search is a near costless venue in which information seeking carries a dramatically lower stigma than self-reported surveys or in-person interviews. Furthermore, as the most common digital footprint [29], internet search logs offer a solution to the challenge of measurement in depression research and practice, as they allow for a nearly costless general assessment of the public health trends. Indeed, the depression-related search can capture both comprehensive and timely data regarding depression over a wide geographic area, and do so for a protracted period, a notion aligned with extant IS and public health research using search query data [17, 18, 22, 29, 45, 47, 80, 108]. In this study, we are further able to examine the coverage and accuracy of our proposed depression-related measures by expanding the set of search terms using the "Crowd-Squared" approach [18], and by correlating depression-related search trends with the regional and national depression data monitored, collected, and compiled by the health administrations (CDC and GHDx). Cross-validations corroborate the fact that depression-related internet search is strongly correlated with objective, and previously corroborated, measures of the local incidence rate of depression.

Contributions and Implications for Practice and Public Policy

Practical and public policy implications stem from this work. First, for mobile game or app developers, we show that the game design encouraging physical activity, offline socialization, and exposure to nature may bring a windfall of public health benefits and potential publicity. This suggestion indicates promising directions for game developers to incorporate these behavioral mechanisms into the design of mobile games or apps. In addition, to the extent that such positive health benefits for users may serve as valuable selling points, notably among parents who have expressed concerns about the potential adverse effects of video games on their children, mobile game and app developers may be able to reap nontrivial economic benefits from the inclusion of above-mentioned features in their games and apps. Last, due to the attractiveness and cost of incorporating these design features, such changes may allow gaming companies to cater to a wider customer base, thereby expanding the accessibility and utilization of their games.

Second, for public health officials, we highlight an attractive option in efforts to track and curtail population-level depression. As discussed, mobile apps are favorable because of their ease of use, low cost, and ubiquitous accessibility, as opposed to more expensive traditional efforts by governments, communities, and physicians. While further corroboration is essential to assess any effect in the long-term, location-based mobile gaming could be a viable means to nudge positive behavioral changes. Furthermore, its effects not only yield benefits for easing depression but also encourage a healthy lifestyle, that is, being physically active, socializing in person in real life, and connecting to nature. Policymakers should consider paying much more attention to technological approaches like location-based mobile games or apps that have the prospects of coping with depression at a modest cost.

Limitations and Suggestions for Future Work

It is important to note that this research is subject to several limitations that create fruitful opportunities for future research. First, we are unable to observe Pokémon Go usage at the individual level. To reduce the effect of this concern, in Table C-8 in Appendix C, we integrate a large set of search trends for Pokémon Go-related terms (e.g., "pokémon near me," "where to catch pokémon") to approximate the overall Pokémon Go usage level. However, additional work is needed to ensure the robustness of this individual-level finding.

Second, although we theorize as to how location-based mobile gaming might alleviate depression, we can only observe an aggregate (population level) prevalence of the condition (as opposed to the incidence of the disease at the individual level) through the lens of internet search, and we cannot assess the effect on the intensive or extensive margin (i.e., a

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general reduction among all people or certain people no longer searching). Additional analyses are essential in a clinical setting, both to corroborate the presence of the observed effect, and to better capture the underlying behavioral mechanisms. For example, future research could consider conducting randomized controlled trials to evaluate the changes in physical activity, face-to-face socialization, and exposure to nature for individual participants who are assigned to play a location-based mobile game. However, this cannot be achieved in our empirical setup (and unit of analysis) due to the practical limitations of macro-level secondary data.

Third, while the depression indicators based on search query data have merits, including timeliness and a greater reach to a broader population who may be suffering from depression, at least compared to surveys, they may be subject to measurement issues. It is possible that the online information search for depression may not fully capture local trends in depression [6, 7]. The epidemiology literature acknowledges that construct validity is a common issue in internet data studies [36, 62]. However, key validity work (e.g., [17, 48]) shows that, in the absence of alternative data sources, search trend data can capture useful and informative changes in the population interest of certain subjects. In our case, alternative fine-grained secondary data sources for contemporary depression are not available. Nevertheless, we mitigate the concern of representation bias by adopting a Principal Component Analysis to improve the measurement and by accounting for temporal and geographical differences in our econometric analysis. Further, we find a strong correlation between depression-related internet search and offline trends monitored by the United States and the global health institutes. Even so, there exists considerable room for improvement.

Finally, it is worth discussing the reliability of Google location data: Google cannot track the location of searches if they are anonymized or obfuscated (e.g., through a VPN). However, this possibility should not materially bias the estimations for three reasons. First, a hidden search occurs but is rather minimal.³¹ Second, the regional usage of VPNs should be stable week by week for the duration of the sample and will thus be captured by location fixed effects. Therefore, the difference-in-differences estimates will not be biased unless the change in VPN use over time has been correlated with the phased rollout of Pokémon Go. Finally, even if this occurs, the net effect would be to make our estimates more conservative. In other words, the true effect of Pokémon Go would be larger if the regional usage of VPNs has had been captured because untreated locations (without *PokémonGo* treatment) will act as a better counterfactual to the treated locations (with *PokémonGo* treatment).

Conclusion

This work theoretically develops and empirically explores the complex relationship between location-based mobile gaming and local depression trends. Depression is a critical public health and societal problem that is gaining increased attention in medical and population health research. However, these issues have remained largely absent from the IS literature (with some notable exceptions [25, 59]). Whereas in earlier research the social and health effects of IT have been relegated to the spread of public health problems [24, 67] and the contagious effect of lifestyle decisions [4], we hope that this study ushers in a novel and important area of IS research: the potential of technology toward population mental health.

Our study highlights mental health benefits that may be facilitated by technology, and how certain technology, such as location-based mobile games, may encourage healthy behavioral changes, while simultaneously coping with costly societal issues. Future research may include additional phenomena pertaining to digital technology and depression, the underlying behavioral mechanisms, and the design of technological and non-medical approaches to, and the coupling with medical interventions on, other mental health problems besides depression.

We hope this research sparks a new intellectual discourse around technology and mental health in the IS field and hopefully in other literatures. In this way, we hope to gain a deeper understanding of whether, how, and why the design, implementation, and use of digital technologies can gain positive effects on population mental health and bring about other broader societal benefits by helping to promote and facilitate a healthy lifestyle.

Notes

- 1. http://www.theguardian.com/commentisfree/2016/jul/13/is-pokemon-go-the-answer-to-obe sity-america.
- 2. http://www.sciencedaily.com/releases/2016/07/160725090154.htm.
- 3. http://www.cnet.com/how-to/pokemon-go-where-its-available-now-and-coming-soon/.
- 4. http://www.washingtonpost.com/news/wonk/wp/2014/12/03/the-google-misery-index-the-times-of-year-were-most-depressed-anxious-and-stressed/.
- 5. There is literature on the negative relationship between general-purpose technology (e.g., email, instant messaging, and social media) and public mental health. Specifically, research has shown that technology may induce feelings of depression in the workplace and people's personal lives [98]. In the workplace, pervasive technology use may cause technostress, that is, stress or psychosomatic illness caused by working with technology [20]. The reasons for technostress include a digital invasion of one's work routine, information overload, the uncertainty and complexity of technology, and insecurity due to rapid technological advances [9, 92, 105, 106]. Research indicates such stressors can reduce job satisfaction, innovation, and productivity [90]. Other negatives that come from technology, such as online social networks [95], have been linked to low self-esteem and jealousy [37]. Steers et al. [98] find that Facebook and depressive symptoms go hand-in-hand, mainly driven by social comparison, which may induce a sense of inferiority and fuel depression. Hence, it is unsurprising that scholars have observed a distinct connection between intense technology use and depression, even suicide [59].
- 6. https://www.ptsd.va.gov/appvid/mobile/ptsdcoach_app.asp.
- 7. https://www.psychiatry.org/patients-families/depression/what-is-depression.
- 8. Pharmacological treatments usually come in the form of antidepressants (e.g., SSRIs), which are designed to regulate levels of dopamine, serotonin, and monoamine oxidase in the body.
- 9. Psychotherapy (i.e., counseling) can help patients who suffer from depression by resolving problematic behaviors, compulsions, or negative beliefs.
- 10. While depression is generally treatable, challenges persist in the efficacy of medical treatments for several reasons [30]. First, complex and compounding depression symptoms increase the uncertainty of a treatment's effect, which may demotivate patients from seeking treatment [43]. Second, treatment may yield adverse side effects. Last, but not least, depression is often attached to a significant social stigma, posing non-trivial challenges to expanding access to necessary mental health care [61].
- 11. Frequent exercise can stimulate the release of endorphins, which contributes to phenomena like the "runner's high [13]."
- 12. http://news.stanford.edu/2015/06/30/hiking-mental-health-063015/.

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 - 13. PokéStops provide players with items, such as Poké balls, eggs, berries, and potions. These PokéStops can be equipped with items called "lure modules", which attract wild, and occasionally rare, Pokémon creatures.
 - 14. PokéGyms serve as battle locations for the team-based king of the hill matches.
 - 15. States/regions are the most granular location units designated by Google Trends.
 - 16. We discuss the contentious issues of using search trends and validate our search-based measure using administrative datasets later. The scope of our findings is discussed in the subsection, *"Enhancing Depression Measurement."*
 - 17. We thank the anonymous reviewer for the valuable feedback, which allows us to better clarify the details of data collection.
 - 18. For example, in the Google Trends data, an index value of 50 for "depression" on July 5, 2016, and an index value of 30 for "depression" on August 5, 2016, show a relative decrease of 20 because 50 and 30 are the values (that indicate the level of search volume) relative to the same baseline (the peak value), 100 on May 5, 2016.
 - 19. As Google Trends only allows to retrieve no more than five queries in tandem, we retrieve each query one request at a time (but all queries retrieved within one day) and standardize them all together to increase comparability across queries.
 - 20. India is the world's second largest English-speaking country (See www.bbc.com/news/maga zine-20500312), and over 58 percent of the Pakistani population speaks English (the state lingua franca) (See www.worldatlas.com/articles/english-speakers-by-country.html).
 - 21. We drop the search term "pain" because it is more likely a symptom of physical health issues.
 - 22. Note that population migration should also not bias the estimate unless populations are moving internationally in a way that is correlated with the release of Pokémon Go (at the country level; see Table 1), which is unlikely.
 - 23. In unreported analyses, we also use region-specific time trends to allow idiosyncratic trends for each location (e.g., cost changes in mental healthcare over time). Results remain consistent.
 - 24. Note that not all countries activated the game during their summer (Table 1); for example, countries in the southern hemisphere (e.g., Australia, New Zealand, South Africa). This is thus a benefit of the global difference-in-differences design.
 - 25. We also consider the impact of seasonality by conducting a falsification test in Table C-1 in the Online Supplemental Appendix C wherein we shift treatment forward a year. No evidence of seasonality bias is found.
 - 26. Tables B-1 to B-4 in the Online Supplemental Appendix B presents the correlation/covariance among search terms and the PCA results. As seen in Table B-4 of the Online Supplemental Appendix, the common variance of depression-related terms (i.e., *stress, anxiety, depression, fatigue*) are well summarized by the first principal component (*A_Comp1*) with a cumulative explained variance of 66.51 percent. Figure B-1 of the Online Supplemental material presents a Scree Plot and suggests that the eigenvalue of *A_Comp1* is above the widely-used threshold of 1 for the best count of components ([57], pp. 374). This suggests that the *A_Comp1* is qualified to serve as a composite index of the depression-related search terms.
 - 27. It is also worth considering other depression-related information seeking behaviors by examining trends in self-harm related search before and after the game release. In doing so, we replicate the PCA using [suicide, painless suicide, how to commit suicide, how to kill yourself], but we find no evidence for this relationship (Table B-6 in the Online Supplemental Appendix B). Although the absence of evidence is not necessarily evidence of absence, this does suggest that the game has not yielded changes to more severe forms of depression. This is an important test. While it is plausible that a local-based mobile game might alleviate less severe forms of depression, the suggestion that playing Pokémon Go might help stave off self-harm is untenable.
 - 28. To further validate the measure of depression-related search trends, we use them to predict local depression (measured by the statistics from CDC and GHDx) and evaluate their out-of-sample predictive performance. Two prediction methods are used. First, we select 50 percent random subsamples as training and testing sets, respectively. We then use the 2004–2014 sample as the training set and the 2015-2016 sample as the testing set. Results are shown in

Table B-5 of the Online Supplemental Appendix B. We find the prediction performs well across different datasets, out-of-sample prediction methods, and different sets of predictors (Columns 4-7). In addition to results from Table 8, this further corroborates that the depression-related search terms are reliable to model the objective offline depression trends that are well captured within administrative mental health datasets.

- 29. The new terms for physical activities are "running," "hiking," "jogging," "biking," "swimming," "trail," "yoga," "outside." The new terms for offline socialization are "fun," "restaurant," "party," "laughing," "dinner," "eating," "conversation," "places". The new terms for exposure to nature are "hiking,", "trail," "park," "animal," "places," "forest," "meditation," "green," "environment." See the Online Supplemental Appendix D for more details.
- 30. We thank an anonymous reviewer for suggesting this analysis and potential proxies. Obesity rate (percent) is the proportion of the population that is obese. The data are from *The World Factbook* by Central Intelligence Agency in 2016. Population density (people per sq. kilometers) is from World Bank data in 2016. Park & Green Space is the average search interest of *"park"* on Google in 2015 (one year before the release of Pokémon Go), which represents the willingness to access public green space.
- 31. In the year of 2016 which we focus on for the empirical analysis, fewer than 4 percent of Americans use VPNs to access online content (https://bigdata-madesimple.com/vpn-use-and-data-privacy-stats-for-2016/).

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Systems Research (ISR), Journal of Management Information Systems, Journal of Marketing, Journal of Marketing Research, Journal of the Academy of Marketing Science, and Journal of the Association of Information Systems (JAIS), among others. Dr. Pavlou is a Senior Editor at ISR, and earlier at MISQ and JAIS. Dr. Pavlou has won several Best Paper recognitions for his research.

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